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Combined influence of multiple climatic factors on the incidence of bacterial foodborne diseases

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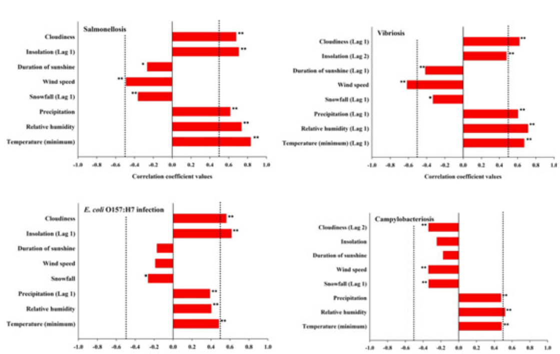
HIGHLIGHTS

- Multiple climatic factors can influence bacterial foodborne diseases (FBD) incidence.
- Relationships between 8 climatic factors and 13 bacterial FBD incidences were analyzed.
- Temperature, relative humidity, precipitation, insolation, and cloudiness were noted.
- These results are useful in designing preventive strategies for FBD.

GRAPHICAL ABSTRACT



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ABSTRACT

Information regarding the relationship between the incidence of foodborne diseases (FBD) and climatic factors is useful in designing preventive strategies for FBD based on anticipated future climate change. To better predict the effect of climate change on foodborne pathogens, the present study investigated the combined influence of multiple climatic factors on bacterial FBD incidence in South Korea. During 2011–2015, the relationships between 8 climatic factors and the incidences of 13 bacterial FBD, were determined based on inpatient stays, on a monthly basis using the Pearson correlation analyses, multicollinearity tests, principal component analysis (PCA), and the seasonal autoregressive integrated moving average (SARIMA) modeling. Of the 8 climatic variables, the combination of temperature, relative humidity, precipitation, insolation, and cloudiness was significantly associated with salmonellosis ($P < 0.01$), vibriosis ($P < 0.05$), and enterohemorrhagic *Escherichia coli* O157:H7 infection ($P < 0.01$). The combined effects of snowfall, wind speed, duration of sunshine, and cloudiness were not significant for these 3 FBD. Other FBD, including campylobacteriosis, were not significantly associated with any combination of climatic factors. These findings indicate that the relationships between multiple climatic factors and bacterial FBD incidence can be valuable for the development of prediction models for future patterns of diseases in response to changes in climate.

1. Introduction

Climate change has an impact not only on crop production and food security but also on food safety and the incidence and prevalence of foodborne diseases (FBD) (Gregory et al., 2005). Several studies have

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suggested an association between climate change or conditions and bacterial FBD (Jacxsens et al., 2010; Kim et al., 2015; Semenza and Menne, 2009), including salmonellosis (Kovats et al., 2004), vibriosis (Craig et al., 2012), pathogenic *Escherichia coli* infections (Liu et al., 2013), and campylobacteriosis (Kovats et al., 2005).

Most research to date has focused on specific climatic factors (either alone or in a combination of two variables) instead of the combined effect of many climatic factors. However, there are many climatic factors that can affect the incidence of foodborne illness (Semenza et al., 2012; Tirado et al., 2010), and the relationships between FBD and the majority of climatic factors, except temperature and rainfall (or relative humidity), remain poorly understood. Understanding the combined influence of climate variability on foodborne illness may improve the ability to predict the effect of climate change on these diseases (Young et al., 2015). Furthermore, regional differences in climatic variables likely affect the regional presence of foodborne pathogens (Kim et al., 2015) and, therefore, the incidence of foodborne illnesses and FBD outbreaks (Patz et al., 2005). South Korea is a small territory with a complex terrain and four seasons; its climate is affected by numerous meteorological factors. Therefore, an assessment of the impact of climate factors on human health is very important to establish national environmental health policies.

The aim of the present study was to examine the combined effects of 8 climatic factors, used to indicate regional climate variability, and the monthly incidence of 13 bacterial FBD in South Korea during 2011–2015.

2. Methods

2.1. Climate data and region

The 8 climatic factors were temperature (mean minimum, mean, and mean maximum), relative humidity, precipitation, snowfall, wind speed, duration of sunshine, insolation, and cloudiness (Supplementary Fig. S1), based on data published by the Korea Meteorological Administration (KMA, 2016). Based on the monthly bacterial FBD incidence data from the Health Insurance Review and Assessment Service (HIRA), we calculated mean values for the climatic factors for each month from January 2011 to December 2015. The included regions of South Korea are positioned between latitudes of 33°06′ and 38°27′ and longitudes of 125°04′ and 131°52′. South Korea is part of the East Asian monsoonal region, and the country has a temperate climate with 4 distinct seasons.

2.2. Bacterial foodborne disease incidence data

Data regarding bacterial FBD cases for 2011–2015 were obtained from the HIRA (2016) using the method by Park et al. (2015), which considered accurate diagnoses based on the 10th Revision of the International Classification of Diseases (ICD-10) codes for 13 foodborne pathogens (*Salmonella* spp., *Shigella* spp., enteropathogenic *E. coli* [EPEC], enterotoxigenic *E. coli* [ETEC], enteroinvasive *E. coli* [EIEC], enterohemorrhagic *E. coli* [EHEC] O157:H7, *Campylobacter* spp., *Yersinia enterocolitica*, *Staphylococcus aureus*, *Clostridium perfringens*, *Vibrio parahaemolyticus*, *Bacillus cereus*, and *Listeria* spp.) (Supplementary Table S1 and Supplementary Fig. S2). The estimated bacterial FBD cases were then grouped on a monthly basis according to inpatient stays (i.e., hospitalizations) and outpatient visits. However, the pre-analysis resulted in a higher correlation between inpatient data and climatic variables than with the outpatient data or the sum of outpatient and inpatient data; therefore, we used only inpatient data for the analysis.

2.3. Statistical analysis

Fig. 1 shows the statistical process used for analyses. First, to quantify the strength of associations between climatic factors and the incidence of bacterial FBD, the Pearson correlation analysis was conducted. This pre-analysis indicated the correlation with each of the climatic factors decreased rapidly 2 months before the FBD cases; therefore, we used climatic data from 2 months prior to the FBD outbreak to account for this time lag. Second, to investigate the multicollinearity between climatic factors and bacterial FBD incidence, variance inflation factors (VIFs) were calculated; eliminating or combining factors with VIF values >10, which are indicative of high multicollinearity (O'brien, 2007).

Next, principal component analysis (PCA) was used to reduce the effect of higher order multicollinearity, investigate the combined effects of climatic variables on bacterial FBD, and explore the structure that identifies the similarities and differences in the climatic data. PCA reduces and extracts the dimensionality of the data and rates the variation present in the original data set, as much as possible (David, 2002). As a result, the manifest variables, and the set of components are reduced to new components called PC1, PC2, and PC3 (for the first, second, and third principal components, respectively), and so on, that are independent and decrease the amount of variance from the original data set. PC1 captures most of the variance, PC2 captures the next highest variance, and so on, until all of the variances are accounted for (Edwards, 1991).

Finally, to determine the relationship between the climatic variables and the time-series FBD incidence data, the seasonal autoregressive integrated moving average (SARIMA) model was used to estimate the parameters of the regression model through pre-processing (log transformed and differenced) of a stationary time series. SARIMA handles time-series modeling and forecasting by taking into account the impact of seasonality and autocorrelations (Helfenstein, 1996). A SARIMA model can be described as ARIMA (p, d, q) multiplied by (P, D, Q) and is defined by Eq. (1) (Suhartono, 2011).

$$\varphi_p(B)\Phi_p(B^s)(1-B)^d\left(1-B^S\right)^D Z_t = \theta_q(B)\Theta_Q\left(B^S\right)a_t \quad (1)$$

where:

$\phi_p(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \cdots - \varphi_p B^p$
$\Phi_p(B^s) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$
$\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$
$\Theta_Q(B^S) = 1 - \Theta_1 B - \Theta_2 B^{2S} - \cdots - \Theta_Q B^{QS}$

where B is the backward shift operator, d and D is the non-seasonal and seasonal order of differences, respectively and usually abbreviated as SARIMA (p,d,q)(P,D,Q). The terms p, d, and q represent ordinary components, where p denotes the AR (autoregression), d the differencing order, and q is the MA (moving average) order that was used. The terms P, D, and Q represent seasonal components, where P denotes the seasonal order of AR, D the differencing order, and Q the MA order that was used. These terms were determined by the autocorrelation function (ACF) and partial autocorrelation function (PACF). The Akaike Information Criterion (AIC) and log-likelihood were used to assist the model fits, and the residuals were further examined for autocorrelation by scatter plots and the figures of ACF and PACF (Hu et al., 2007).

All analyses were performed using the SPSS 12.0 (Data Solution Inc., Seoul, South Korea), and $P = 0.05$ was considered significant.

3. Results

In the correlation analysis, 9 of the 13 bacterial foodborne pathogens (*Shigella* spp., EPEC, ETEC, EIEC, *Yersinia enterocolitica*, *Staphylococcus aureus*, *Clostridium perfringens*, *Bacillus cereus*, and *Listeria* spp.) were not correlated ($P > 0.05$) or had a weak correlation with most of the climatic factors. The remaining 4 bacterial foodborne pathogens (*Salmonella* spp., EHEC O157:H7, *Campylobacter* spp., and *Vibrio parahaemolyticus*) showed relatively high correlation with a majority of the climatic factors (Supplementary Table S1).

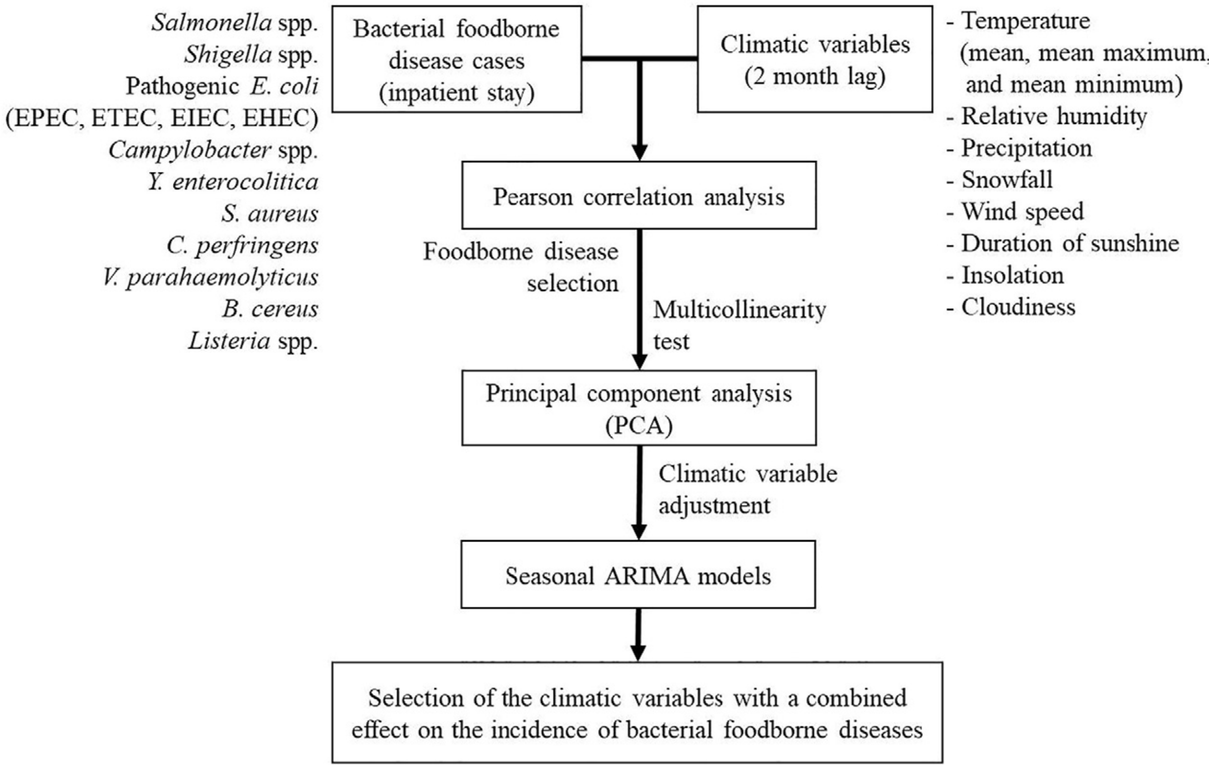

Fig. 1. The advanced statistical process to investigate the combined effect of 8 climatic factors on the monthly incidences (hospitalizations) of 13 bacterial foodborne diseases in South Korea from January 2011 to December 2015. ARIMA: autoregressive integrated moving average.

The four highly correlated bacterial foodborne infections (Fig. 2 and Supplementary Figs. S3–S6) showed different correlations. While salmonellosis significantly correlated with all climatic factors ($P<0.01$), including duration of sunshine ($P<0.05$); vibriosis significantly correlated with all climatic factors ($P<0.01$), including wind speed ($P<0.05$). EHEC O157:H7 infection significantly correlated with cloudiness, insolation, precipitation, relative humidity, minimum temperature (all, $P<0.01$) and snowfall ($P<0.05$), but its correlation with wind speed and duration of sunshine were not significant ($P>0.05$). Campylobacteriosis also significantly correlated ($P<0.01$) with all climatic factors except the duration of sunshine and insolation ($P>0.05$).

Relative humidity and mean minimum temperature (lag 1) had high multicollinearity for salmonellosis and vibriosis, respectively, and they were combined by PCA. None of the factors exhibited multicollinearity for EHEC O157:H7 infection or campylobacteriosis. All temperature variables (mean temperature, mean maximum temperature, and mean minimum temperature) had high multicollinearity. Since mean minimum temperature had a relatively high correlation, it was the most appropriate climatic variable for temperature.

As a result of the PCA, some of the climatic variables were closely associated and could be constructed as 2 new components for each of the 4 highly correlated FBD (Table 1). Based on the SARIMA model, the best regression models for salmonellosis, vibriosis, EHEC O157:H7 infection, and campylobacteriosis that had the highest correlation values for monthly incidence were ARIMA $(2, 1, 0)\ (1, 0, 0)_{12}$ with AIC = 13.7, ARIMA $(1, 0, 0)\ (0, 1, 0)_{12}$ with AIC = 58.2, ARIMA $(0, 0, 0)\ (1, 1, 0)_{12}$ with AIC = 85.8, and ARIMA $(1, 1, 0)\ (0, 1, 0)_{12}$ with AIC = 41.1, respectively (Table 2). An analysis of the residuals showed the goodness of fit among randomly distributed residuals with no autocorrelation (Supplementary Figs. S7–S10).

As shown in Table 2, the first components of the combined factors were significant for salmonellosis, vibriosis, and EHEC O157:H7 infection (Sal_PC1, $P<0.01$; Vib_PC1, $P<0.05$; and Eco_PC1, $P<0.01$, respectively), while the second components were not significant. Neither component 1 nor 2 was significant for campylobacteriosis ($P>0.05$).

4. Discussion

Only 4 (*Salmonella* spp., EHEC O157:H7, *Campylobacter* spp., and *V. parahaemolyticus*) of the 13 foodborne pathogens included in the present study had relatively high correlations with the 8 climatic factors in South Korea during 2011–2015. The combination of temperature, relative humidity, precipitation, insolation, and cloudiness correlated positively with salmonellosis, vibriosis, and EHEC O157:H7 infection, but not with campylobacteriosis. Snowfall, wind speed, and duration of sunshine were found to be negatively associated with salmonellosis, vibriosis, EHEC O157:H7 infection, and campylobacteriosis (Fig. 2). The relationships between bacterial FBD and temperature and relative humidity (or precipitation) have been extensively investigated for incidences of salmonellosis (Kovats et al., 2004; Semenza and Menne, 2009), and vibriosis (Craig et al., 2012) in Europe, and for EHEC O157:H7 outbreaks in Canada (Fleury et al., 2006). The results for temperature and humidity from these two countries were similar to those from South Korea.

Since climatic variables may not always affect foodborne infection directly, their lagged effects on the incidences of FBD were studied in the present study as well as in an earlier study (Lake et al., 2009). We found that except for wind speed, all climatic factors had a strong time-lag effect on vibriosis was found to have for vibriosis, and might play an important role in the prevention of vibriosis in South Korea. However, Zhang et al. (2010) suggested that lagged effects of meteorological variables on foodborne infection vary by regions and pathogens. In addition, a variety of related factors (e.g., food processing or intake, etc.) may also affect the lagged effect, and further research is needed to determine these factors. Another interesting finding was that most

of the bacterial pathogens showed a slightly higher correlation with the mean minimum temperature when compared to the mean temperature or the mean maximum temperature, although the cause is currently unclear. It is possible that the occurrence of bacterial FBD is affected more by the minimum temperature. Additionally, most of the bacterial FBD had slightly stronger correlations with relative humidity than with precipitation.

Despite the reported influence of the combination of multiple climate change factors on FBD (Kurane, 2010), specific examples are lacking. Based on the PCA and SARIMA models in the present study, there appears to be a combined effect of these climatic variables and on incidences of 3 bacterial FBD in South Korea. Specifically, salmonellosis, vibriosis, and EHEC O157:H7 infections were influenced by insolation and cloudiness in addition to temperature, relative humidity, and precipitation. Given these results, the combination of increased insolation and cloudiness is an important factor for some bacterial FBD. Although only 8 climatic factors were evaluated in this study, other climatic factors (e.g., water salinity in vibriosis) may also have an influence on the incidence of FBD in South Korea.

Although most foodborne pathogenic bacteria are vulnerable to solar radiation (insolation), Jenkins et al. (2011) reported that EHEC O157:H7 appeared to be resistant to insolation in pond water, whereas Ferens and Hovde (2011) noted that the extra-intestinal prevalence of EHEC in animal reservoirs was reduced by high insolation. However, the present results indicate that increased insolation in combination with other climatic factors (e.g., increasing temperature) has a greater impact on the prevalence of FBD by itself. For example, Kim et al. (2013) suggested that pathogens in stored food in a car trunk could be related to the higher radiation associated with increasing food temperatures.

Warmer air can hold more moisture, causing increases in cloud cover and total precipitation (Curriero et al., 2001). Cloudiness is the highest in August in South Korea (Supplementary Fig. S1), and higher clouds generally warm up, while lower clouds cool down. Although no

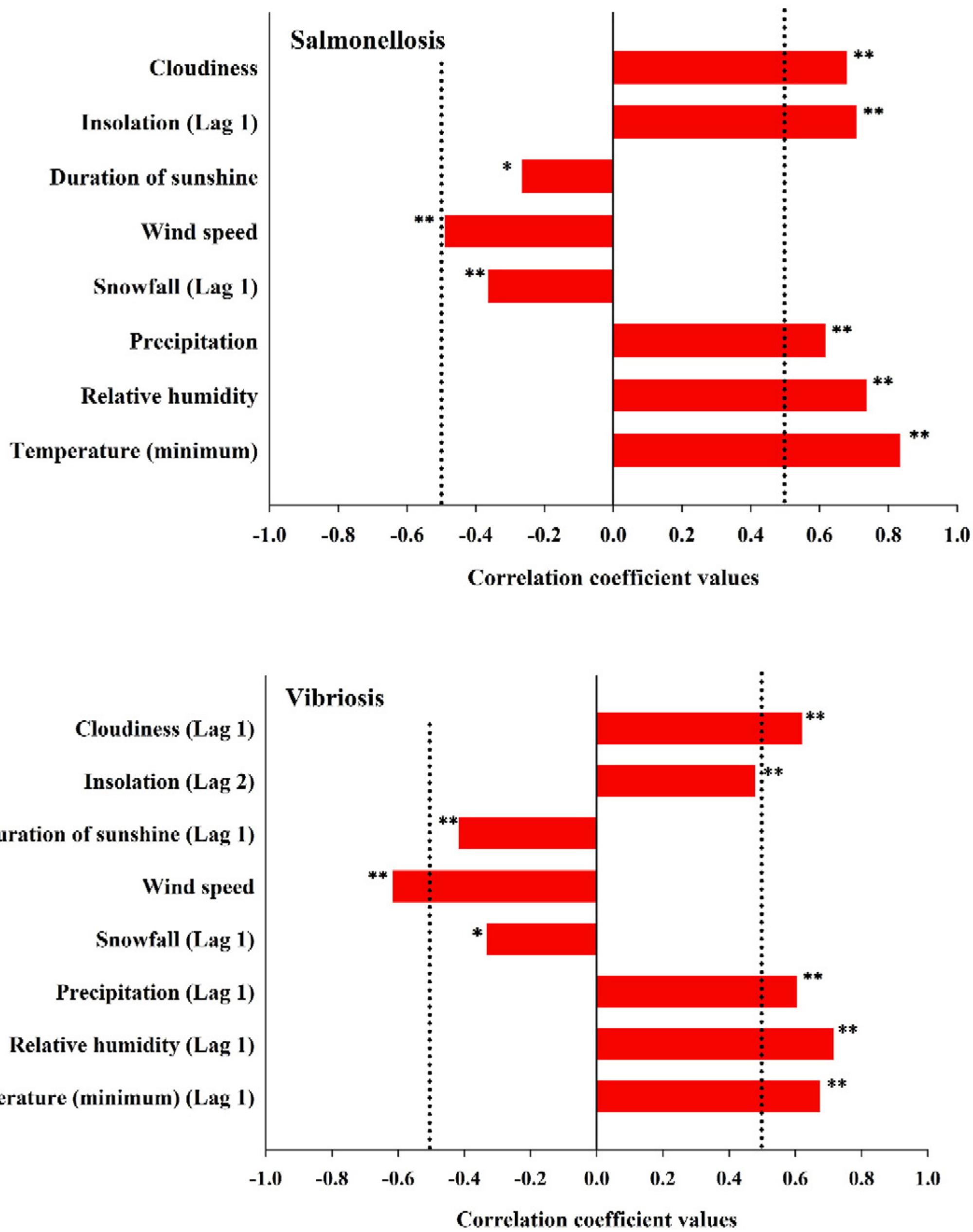

Fig. 2. Correlations between 8 climatic factors and the monthly incidences (hospitalizations) of 4 bacterial foodborne diseases in South Korea from January 2011 to December 2015. Lag 1: one month prior, Lag 2: two months prior, $^{*}P < 0.05$; $^{**}P < 0.01$.

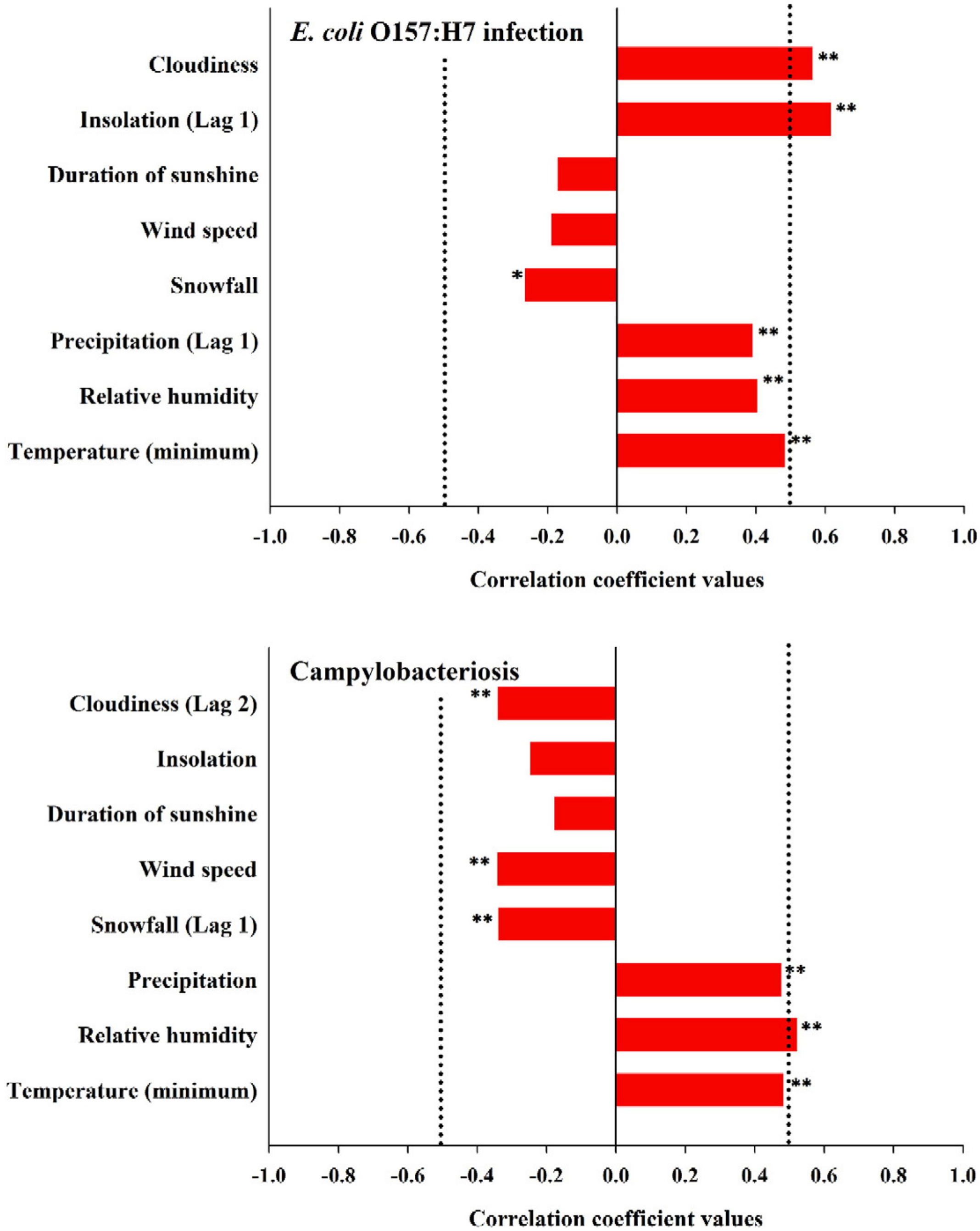

Fig. 2 (*continued*).

study has demonstrated a direct relationship between cloudiness and bacterial FBD, the present study showed positive correlations between cloudiness and salmonellosis, vibriosis, and EHEC O157:H7 infection. In South Korea, cloudiness is directly related to the rainy season. The combined effect of increased rainfall and relative humidity is therefore, likely to be important for the increase in these 3 bacterial FBD (Table 1).

Snowfall, duration of sunshine, and wind speed did not emerge as important combined climatic factors for bacterial FBD. However, Shaw et al. (2014) reported that wind speed (during a storm event) was positively associated with *Vibrio* spp. density changes in the Chesapeake Bay, USA. In the present study, wind speed, on its own and without a time lag, was negatively associated with the incidences of salmonellosis, vibriosis, and campylobacteriosis. In South Korea, wind speed is the lowest in September and the highest in May (Supplementary Fig. S1). Because of the lack of a combined influence on the incidence of bacterial FBD, additional research is required to explore the relationship of wind speed with FBD.

The risk of campylobacteriosis has been positively associated with temperatures, although the strength of the association was not consistent in all studies (Kovats et al., 2005; Louis et al., 2005; Patrick et al., 2004). However, at the time, information was sparse on the relationship between environmental temperatures and *Campylobacter* infections in humans, and neither study was adjusted for seasonal factors that could confound the association between campylobacteriosis and temperature. The present study did not find a strong effect of climatic factors, including temperature variability, on *Campylobacter* transmission; this might suggest that there are regional differences in the effect of climatic factors on the incidence of bacterial FBD.

Despite a global climate change and an increase in global air temperatures (IPCC, 2014), the incidences of some bacterial FBD have declined

Table 1
Principal component analysis (PCA) for monthly climatic variables on the monthly incidence of inpatient stays (hospitalizations) for 4 types of foodborne diseases in South Korea from January 2011 to December 2015.

Bacterial foodborne diseases	Components	Combined climatic variables	% of variance
Salmonellosis	Sal_PC1	Mean minimum temperature, Relative humidity, Precipitation, Insolation (Lag 1), Cloudiness	54.1
	Sal_PC2	Snowfall (Lag 1), Wind speed, Duration of sunshine, Cloudiness	16.7
Vibriosis	Vbr_PC1	Mean minimum temperature (Lag 1), Relative humidity (Lag 1), Precipitation (Lag 1), Insolation (Lag 2), Cloudiness (Lag 1)	54.9
	Vbr_PC2	Snowfall (Lag 1), Wind speed, Duration of sunshine (Lag 1), Cloudiness (Lag 1)	18.3
EHEC O157:H7 infection	Eco_PC1	Mean minimum temperature, Relative humidity, Precipitation (Lag 1), Insolation (Lag 1), Cloudiness	57.8
	Eco_PC2	Snowfall, Insolation (Lag 1), Cloudiness	21.3
Campylobacteriosis	Cam_PC1	Mean minimum temperature, Relative humidity, Precipitation, Cloudiness (Lag 2)	58.0
	Cam_PC2	Precipitation, Snowfall (Lag 1), Wind speed	18.7

EHEC: enterohemorrhagic *Escherichia coli.*

in Europe over the previous decade (Semenza et al., 2012), due, in part, to human intervention (Smith et al., 2015). Improved health promotion, as well as food and water safety interventions and policies, may counteract the negative impact of climate change on public health. The mechanisms underlying the observed relationships between FBD incidence and climate change are not fully understood, but they are likely to be the result of a complex interplay of different factors, including human behavior and consumption patterns, pathogen prevalence in animal reservoirs, and pathogen survival patterns in the environment (Kim et al., 2015). Such phenomena could be projected, explored, and assessed in detail using quantitative microbial risk assessment (QMRA) models (Janevska et al., 2010; Smith et al., 2015).

The differences between our results and other studies could be due to regional differences in weather conditions or the use of different data (e.g., FBD outbreak, inpatient data, or outpatient data). Compared to a previous study that investigated the relationship between FBD outbreak data and climatic factors (Kim et al., 2015), our inpatient data revealed a higher correlation with temperature and relative humidity, likely because the outbreak data did not fully capture the incidence of FBD. In the present study, inpatient data showed a higher correlation with climatic variables than outpatient data or the sum of these data; however, to more precisely measure these associations, smaller units of time (e.g., weeks instead of months) might be helpful (Kovats et al., 2005). In addition, the use of only 5 years of data might have limited the number of patients; however, advanced statistical methods (PCA and SARIMA) were used to overcome this shortcoming. Further, the effects of extreme weather conditions (e.g., high temperatures, torrential rain, and drought) on the incidence of FBD were not considered, and these should be studied in the future.

Table 2
Regression coefficients of the chosen seasonal autoregressive integrated moving average (SARIMA) models with the new components listed in Table 1 on the monthly incidence of inpatient stays (hospitalizations) for 4 types of foodborne diseases in South Korea from January 2011 to December 2015.

Foodborne diseases and climatic variables	Model		
	β	SE	*P*-values
Salmonellosis (AIC = 13.7, Log-likelihood = −1.8) (2, 1, 0) $(1, 0, 0)_{12}$			
AR1	−0.4664	0.1395	0.0015
AR2	−0.3677	0.1409	0.0118
SAR1	0.4189	0.1424	0.0048
Sal_PC1[a]	0.2373	0.0458	0.0000
Sal_PC2[a]	−0.0325	0.0392	0.4101
Vibriosis (AIC = 58.2, Log-likelihood = −26.1) (1, 0, 0) $(0, 1, 0)_{12}$			
AR1	0.5657	0.1450	0.0006
Vib_PC1[a]	0.6623	0.2841	0.0275
Vib_PC2[a]	0.0408	0.1970	0.8375
EHEC O157:H7 infection (AIC = 85.8, Log-likelihood = −39.9) (0, 0, 0) $(1, 1, 0)_{12}$			
SAR1	−0.6993	0.1209	0.0000
Eco_PC1[a]	1.1324	0.3261	0.0015
Eco_PC2[a]	−0.0475	0.1303	0.7179
Campylobacteriosis (AIC = 41.1, Log-likelihood = −17.6) (1, 1, 0) $(0, 1, 0)_{12}$			
AR1	−0.7596	0.1310	0.0000
Cam_PC1[a]	0.1627	0.2677	0.5539
Cam_PC2[a]	0.1509	0.1453	0.3182

AIC, Akaike Information Criterion; AR1, first-order autoregression; AR2, second-order autoregression; SAR1, first-order seasonal autoregression.
[a] See Table 1.

5. Conclusions

In conclusion, this study finds a correlation between the incidences of 4 of the 13 bacterial FBD (based on hospitalization) and 8 climatic factors after a 1- or 2-month lag in South Korea. The combination of climatic factors including temperature, relative humidity, precipitation, insolation, and cloudiness emerged as potential forecast factors for salmonellosis, vibriosis, and EHEC O157:H7 infection. Public health initiatives should consider the local climate conditions when planning prevention strategies for bacterial FBD. The statistical analysis used in this study could be useful for determining the effects of climate change on FBD patterns using QMRA. Moreover the relationships between various climatic factors and the national incidences of bacterial FBD could contribute to the development of prediction models for future patterns of diseases based on climate change.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.scitotenv.2017.08.045.

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